A Study on Change Detection in Hyperspectral Image

A thesis submitted in partial fulfilment of the requirement for the degree of

Master of Technology

In

Electronics and Communication Engineering

Specialization: Signal and Image Processing

By

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Under the Guidance of

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Rourkela, Odisha, 769008, India

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CERTIFICATE

This is to certify that the work done in the thesis entitled **A study on Change Detection in Hyperspectral image** by **Manda Sreevalli** is a record of an original research work carried out by her in National Institute of Technology, Rourkela under my supervision and guidance during 2014-2015 in partial fulfilment for the award of the degree in Master of Technology in Electronics and Communication Engineering (Signal and Image Processing), National Institute of Technology, Rourkela.

Place: NIT Rourkela

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DECLARATION

I certify that,

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c. I have followed the guidelines prescribed by the Institute in writing my thesis.

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Manda Sreevalli

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Abstract

Change detection is the procedure of obtaining changes between two Hyperspectral pictures of same topographical zone taken at two unique times. It conveys the essential and important change data of a scene. Due to a breakthrough in Hyperspectral remote sensing Hyperspectral remote sensors can capable of producing narrow spectral resolution images. These high resolution spectral and spatial hyperspectral images can find small variations in images. This work describes an efficient algorithm for detecting changes in Hyperspectral images by using spectral signatures of Hyperspectral images. The objective is developing of a proficient algorithm that can show even small variations in Hyperspectral images. It reviews Hierarchical method for finding changes in Hyperspectral images by comparing spectral homogeneity between spectral change vectors. For any scenery locating and also exploration regarding adjust delivers treasured data regarding achievable changes. Hyperspectral satellite detectors get effectiveness throughout gathering data with large spectral rings. These types of detectors typically deal with spatially and also spectrally high definition graphics and this can be used by adjust discovery. This particular function is actually elaborated and also applied your adjust discovery procedure by simply controlling Hyperspectral graphics. The main aim with this thesis is actually studying and also constructing of Hyperspectral adjust discovery algorithms This kind of analysed approach is really applied to assess Hyperspectral picture image resolution files along with the approach analysed in this particular thesis is really change breakthrough making use of Hierarchical method of spectral change vectors and also making use of principal ingredient examination and also k-means clustering. This particular document offers applying and also verify of trends Hyperspectral image.

Contents

List of Figures

List of Tables

Chapter 1
Introduction

1. Introduction

Change discovery in Hyperspectral pictures is finding of worldly distinction between those pictures. Change operation on the symbolism information suggests the discovery of an arrangement of pixels that have experienced a noteworthy change generally in a past information. Reason for Change identification will be distinguishing proof of the arrangement of pixels that are bizarrely distinctive among the picture grouping. Two unique sorts of changes exist in change discovery those are vast scale and little changes. To recognize huge scale changes extensive measure of data is not obliged and can be effortlessly noticeable. Huge scale changes can recognize utilizing Color and multispectral pictures [1]. More data of the picture is needed for recognizing little changes and that can be gotten from Hyperspectral pictures.

A Hyperspectral picture can give more data of picture pixel. Hyperspectral imaging is utilized as a part of distinctive applications like Disaster checking of violent winds, snow slides, woodland fires, environment observing, and military target observing and outskirt observation. Change location is the worldly distinction between two Hyperspectral pictures of same geological territory of getting at same wavelength groups [2]. Normally one pixel in Hyperspectral image describes the area of one kilometer pixel.

One Hyperspectral image at various wavelength bands describes nearly a thousand kilometers of geographical area. Possibility of some percent of one pixel exhibits change, whereas another part of same pixel may not exhibit a change since one pixel depicts nearly one kilometer area. So the task is finding of change endmembers even within an individual pixel by using spectral signatures of pixels. Changes can detect either by supervised change detection or by unsupervised change detection. For supervised change detection a reference data set of images is required [3]. But obtaining of a reference data set of images is difficult in the case of

Hyperspectral remote sensing images. Numerous military and regular citizen applications exists for the recognition or following of objects of enthusiasm for a remotely detected picture. Contingent upon innovation and mission necessities one valuable methodology is change discovery. Utilizing change disclosure, two photos of the same scene at deferent times, presumably under deferent conditions, are mishandled for the area of changes within the photo [3].

Change location fills two needs: first to identify changes in the picture, and second to decrease the false caution rates in the identification of particular targets. The utilization of pictures at deferent times aides dispense with the superfluous data and spotlights on the regard between the two times. Two sorts of changes are quite compelling in change discovery: substantial scale changes and little peculiar changes [3]. Extensive scale changes are generally simple to identify and a lot of data for the scene are not needed. Change recognition calculations for vast scale changes can for the most part be actualized on shading or multispectral pictures.

The location of little, uncertain targets requires more data about every pixel obtained through the utilization hyperspectral pictures. Unsupervised change location is a procedure that makes an immediate examination of a couple of remote detecting pictures procured on the same land territory at diverse time cases keeping in mind the end goal to recognize changes that may have happened. Unsupervised change recognition methods don't have to unequivocally distinguish the sorts of area cover or area utilization moves that have occurred in the district of concern [3].

Consequently, these systems are suitable for applications, for example, recognition of deforestation or smoldered regions, for instance [4]. The execution of unsupervised procedures are for the most part corrupted by a few components, for example, brightening varieties, environmental condition changes and sensor alignment, which regularly caused at diverse procurement times [4]. Remote detecting symbolism by and large requires certain redresses because of undesirable sensor qualities and other irritating impacts before performing information investigation. Normal rectifications incorporate clamor decrease, radiometric adjustment, sensor alignment, environmental rectification, sun oriented redress, topographic amendment, and geometric remedy. In this paper, we accept that progressions between two pictures are just brought about from physical changes acquired in the topographical territory, and those run of the mill rectifications specified already are either playing no issue or having been done on the pictures before applying the proposed change location system [5].

Unsupervised change recognition methods essentially misuse a programmed examination on the progressions (or contrasts) of information which are yielded in view of numerous fleeting pictures procured at diverse time occasions. Picture differencing begins its change location by taking the distinction of the two pictures procured at two distinctive time occurrences to deliver a distinction picture, from which changes are further broke down. The standardized contrast vegetation list methodology abuses the vegetation records or other straight or nonlinear mix of the first groups to direct change investigation.

Change vector investigation methodology decides the heading and size of changes in the multidimensional unearthly space and simultaneously dissects those progressions distinguished in all information layers [5], as opposed to on a couple chose phantom groups. Systems taking into account the important segment examination are utilized to apply key part change on the component space removed from multi-transient pictures of two distinctive time examples independently, or all in all, to perform change discovery. In picture proportioning procedures, the examination made between two otherworldly groups procured at two diverse time occasions is performed by registering their proportion instead of their numerical distinction [6]. The objective of hyperspectral change identification is to and fascinating changes. Intriguing changes is a subjective term characterized by the client, yet hyperspectral change discovery calculations are most valuable in the location of little, abnormal changes between the two time periods. Cases incorporate the insertion, cancellation or development of an object of hobby. Remotely detected pictures normally cover expansive regions of area. Accordingly, the recognition of little protests of enthusiasm inside of a worthy false caution rate can be troublesome. Numerous single pass calculations, for example, the coordinated channel, have been utilized to effectively recognize targets however the false alert rates are still high.

Change discovery calculations can be executed so as to create less false alerts than single pass recognition or help in the identification of little questions that are excessively troublesome, making it impossible to identify inside of single pass pictures. In spite of the fact that change identification enhances the false caution rate of recognition contrasted with single pass methodologies, it additionally presents a few new difficulties of its own. All together for the pictures to be thought about for the recognition of little or sub-pixel focuses on, the pixels in the pictures must be connected [7].

Most change location calculations require exact spatial enlistment between the two pictures so as to analyses them pixel by pixel. Furthermore, the brightening and shadowing differences that outcome from occasional, diurnal or climate changes are more declared when pictures from distinctive times are being looked at. Environmental adjustment does not totally kill these impacts, making them show as differences between the two pictures. Different change discovery calculations endeavor to address these difficulties and in addition troubles, for example, high dimensionality which are characteristic to hyperspectral information. Change recognition is characterized as any procedure that uses numerous information sets of the same scene so as to identify changes.

Much of the time, two pictures of the same scene at diverse times utilizing the same or deferent phantom groups are broke down [8]. The fundamental presumption is that most of the scene stays invariant while just the object of interest changes. Change location can be connected to any picture pair. By definition it doesn't oblige a certain sort of imaging. Calculations have been produced for panchromatic, multispectral, and hyperspectral pictures yet the kind of picture accessible will focus the level of location conceivable.

The reason of hyperspectral imaging expresses that the sun lights up the surface of the earth and for each surface material the measure of light, or radiation, retained, responded, or radiated differs with wavelength. The sun's radiated vitality over every wavelength is alluded to as the sun based range. Sun powered vitality spreads through the climate, associates with the materials being imaged, is consumed, radiated, and afterward reflected in contrasting wavelengths based upon the material [9]. The rejected and transmitted vitality then goes through the air where it is measured by a sensor. The estimation at the sensor is known as the brilliance spectra. How the assimilation shifts with wavelength is known as the unearthly mark. Human improvement and regular powers consistently change scenes. The investigation of these varieties is essential in numerous undertakings, for example, observing area utilization, hazard evaluation, and the examination of overall populace development and advancement. Therefore, change location has an expanding significance in the field of remote detecting.

The pictures procured by periodical goes of remote detecting satellites over the same regions allow a standard examination of the progressions that happened on the ground. The expansive measure of accessible satellite information has driven the remote detecting group to center its consideration on unsupervised change discovery systems, where ground-truth data is a bit much. The high determination in speaking to the reviewed scene makes the logical data an overwhelming component in the high determination pictures [10].

Actually, dissimilar to in low and medium spatial determination pictures, the relations between nearby pixels turn into an essential data hotspot for the comprehension of the scene. The high geometrical determination and the relevant data are components that are especially critical in the urban scenes, opening new points of view for change identification applications. Unsupervised change identification assumes an imperative part in numerous application spaces identified with the misuse of multitemporal pictures.

Contingent on the considered application, the change-identification issue has diverse properties and idiosyncrasies, and ought to fulfill particular imperatives. In a few areas, the need imperative is identified with the need to ensure a constant location of changes (e.g., in feature reconnaissance [1]–[4], movement recognition [5], [6], and so on.). In different applications, the time limitation can be loose and the accuracy of the change-location result (additionally at the expense of a high computational unpredictability) assumes the most imperative part (e.g., remote detecting [7], [8], biomedical applications [9], [10], and so forth.).

For a few areas, the change-identification issue can oblige multidimensional (or multichannel) pictures: this is for occurrence the instance of information all the while obtained in distinctive groups of the electromagnetic range (multispectral pictures) or brought with multimodal procurement conventions (multimodal pictures. Change-location strategies grew in other application spaces for the particular investigation of high determination pictures result ineffectual when connected to remote detecting pictures. The primary issues are identified with the diverse conditions in which the remote detecting pictures can be procured, and specifically to contrasts in: 1) daylight and climatic conditions; 2) sensor obtaining geometry [8], [11], [18]; and 3) otherworldly marks of vegetation because of regular impacts. To diminish the effect of these conditions on change recognition maps, preprocessing steps are needed as: coregistration, radiometric and geometric remedies, and clamor diminishment [10].

Among them, coregistration assumes a basic part and turns out to be more unpredictable and discriminating (and in this manner naturally less precise), when the geometrical determination increments. By and by, an impeccable arrangement between pictures is inconceivable as contrasts in the obtaining perspective points and in geometrical mutilations can't be adjusted, then bringing about a huge remaining enlistment clamor which strongly effects on change location. Another vital issue in change discovery on high determination pictures concerns the displaying of the spatial setting data of the scene. A large portion of the traditional change-recognition methods for the most part expect spatial autonomy among pixels, which is not sensible in high geometrical determination information. With a specific end goal to better adventure the spatial connection among neighboring pixels and to get precise and solid change location maps (both in districts comparing to fringe or geometrical subtle elements and in homogeneous ranges), it is important to coordinate the ghostly data with the spatial one and to model the multiscale properties of the scene.

In the writing just couple of methods fit to endeavor the aforementioned ideas [21]–[24] are accessible. Change Detection in Hyperspectral Imagery goes for recognizing an arrangement of pixels that have experienced a pertinent change concerning a past obtaining. The progressions of hobby are those because of the insertion, development or evacuation of articles in the watched scene. A large portion of the no doubt understood change identification strategies depend on a pixel based correlation between pictures, therefore obliging an exact enrollment, which is truly hard to accomplish when information are gathered by push sweeper sensors introduced locally available airborne stages [13]. Misalignment can without much of a stretch happen because of errors in the remuneration of stage development and in the territory model utilized for georeferencing. This disadvantage might extremely influence change identification exhibitions when managing high spatial determination information [14].

Change identification has vital applications in observing common habitats and human exercises on the earth. Notwithstanding the discovery of changes, change examination may incorporate the recognizable proof of progress sorts and measurement of the measure of progress. Numerous methodologies have been proposed before. There are two noteworthy classifications of progress examination systems: those utilizing the radiometric change or "distinction picture", and those investigating discovery/order results or extricated components. Notwithstanding picture co-enrollment, radiometric standardization is another basic preprocessing step. The goal of radiometric standardization is to minimize the radiometric changes from the variety of climatic conditions, sun powered brightening, and sensor alignment, and so forth.which are insignificant to the real land-spread changes of hobby.

A locale based straight relapse system was proposed for effective radiometric standardization. Presently, the expansive file created by satellite remote-detecting missions is turning into an inexorably significant wellspring of data. This prompts a superior understanding of area cover and area use development by dissecting the ghostly reaction of the distinctive earth's surface components [16]. A far reaching utilization of hyperspectral information includes the demonstrating and the treatment of the ghastly mark (i.e., the graphical representation of the phantom reaction as a component of wavelength). Ordinary arrangement plan utilizes a solitary picture to concentrate a pixel range which will be acclimatized to every endmembers accumulated from ground missions [17].

The majority of these methodologies are in light of the suspicion that the ghostly mark of every area spread sort is constant and uniform over the time. By and by, this supposition does not, tangibly, uncover the considerable spatial and/or transient varieties [18], [19], [20]. Surely, a few variables like soil piece, topographic varieties, and neighborhood barometrical conditions may modify the unearthly reaction starting with one locale then onto the next, despite the fact that they relate to the same class. These days, there is an extraordinary sympathy toward changes to the Earth's surroundings, accordingly, there is a genuine need to search for new investigation devices to help recognize where and when these progressions are happening.

At present, a standout amongst the most critical wellsprings of data is given by satellite pictures. This data is getting to be urgent for some crises, common or synthetic catastrophes, and applications, for example, bramble flames, surges, and oil slicks. The atmosphere and earth sciences have as of late encountered a quick change from an information poor to an information rich environment [21]. Specifically, atmosphere and biological community related perceptions from remote sensors on satellites, and yields of atmosphere or earth framework models from expansive scale computational stages, give terabytes of fleeting, spatial and spatio-worldly information. These huge and data rich datasets offer gigantic potential for propelling the exploration of area spread change, environmental change and anthropogenic effects [21].

One essential region where remote detecting information can assume a key part is in the investigation of area spread change. In particular, the transformation of normal area spread into human commanded spread sorts keeps on being a change of worldwide extents with numerous obscure natural results. Furthermore, it turns out to be vital to take choices in a few regions, for instance rural applications, where there is a need to anticipate product yield, preharvest creation and harvest harm appraisal [22]. The capacity to recognize changes that evaluate fleeting impacts utilizing multitemporal symbolism gives a crucial picture examination apparatus in numerous assorted applications.

Because of the substantial measure of accessible information and broad computational prerequisites, there is a requirement for change identification calculations that naturally think about two pictures taken from the same range at distinctive times and focus the areas of changes. Normally, in the correlation process [22]–[24], contrasts between two relating pixels having a place with the same area for a picture pair are resolved, in light of some quantitative measure. At that point, a change is named if this distinction measure surpasses a predefined limit, and no change is marked, something else. The greater part of the examination methods depicted in [22] just consider data contained inside of a pixel, despite the fact that power levels of neighboring pixels of pictures are known not noteworthy relationship. Likewise, changes are more prone to happen in associated locales as opposed to at disjoint focus. In addition, hyperspectral information, whether acquired via airborne or satellite sensors, is typically gotten over different obtaining conditions.

In such cases, components like bidirectional reflectance can instigate further varieties in the gathered otherworldly marks. Subsequently, these varieties will change the ghostly properties of the same area spread sort which could transform starting with one district then onto the next

[23]. This variability is normally arranged into: intraspecific and interspecific. Evidently, intraspecific variability expands the likelihood of phantom cover with other area spread sorts and makes ghostly segregation utilizing monotemporal pictures troublesome and now and again unthinkable.

1.1. Hyperspectral Imaging

Hyperspectral remote sensors collect data simultaneously at adjacent and narrow spectral bands. Due to narrow spectral resolution each pixel of a Hyperspectral image represents continuous spectrum [25]. These Hyperspectral remote sensing images need atmospheric correction. Hyperspectral remote sensing image spectra has good similarity with laboratory image spectra after adjusting of sensor and atmospheric correction [25]. Advantage of comparison of both spectra obtained remote sense spectrum of Hyperspectral image and laboratory reflectance spectrum is to recognize and map various diagnostic minerals. Several matters reflect some wavelength. A few materials keep or absorb same wavelengths. Different materials are classified by the nature of that materials of reflecting or absorbing. A study of spectroscopy explains the materials reflects what wavelengths and which materials absorbs what wavelength spectral bands [26].

Hyperspectral remote detecting Hyperspectral remote sensors can fit for creating tight determination phantom groups in obvious and infrared wavelength scope of the electromagnetic range. Interpretation and understanding of ground materials require properties of ground materials of what we need to measure since a Hyperspectral image is a wealth information content image

1.2. Imaging spectrometer

Imaging spectrometer instruments produce Hyperspectral images. Hyperspectral sensors are developed by either by spectroscopy or remote sensing technology. These are exploited for making laboratory measurements to a target. The study of light reflected from or emitted by a material and the variation of energy corresponding to energy is called spectroscopy [27].

Digital imagers measure wavelengths in a sequential manner, even for small areas. The above figure depicts obtaining of wavelengths from a pixel cell of Hyperspectral image. The obtaining of wavelength bands depends on limitations of design of detectors and the necessities of

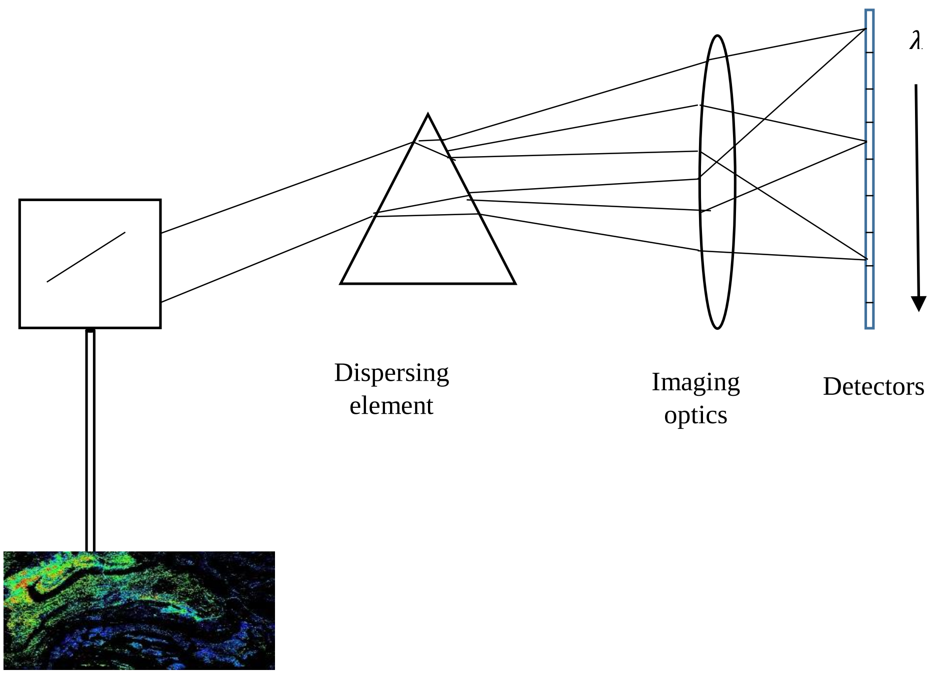

Figure 1-1 Basic elements of an imaging spectrometer

Light is split into narrow and adjacent bands by the prism of Spectrometer. A detector measures the wavelength of these bands. More detectors can measure more spectral bands of wavelength. These can measure the wavelength with in visible and infrared spectral range, nearly 0.3-2.3 micrometers with 0.02 micrometer resolution.

1.3. Spatial Resolution and Mixed spectra

Each pixel in Hyperspectral image denotes a small area of the surface of the Earth and spectral measurements of those pixels can be made by an Imaging spectrometer. Spatial determination of the picture is the otherworldly estimation of size of ground range. If the size of ground cell is more spatial resolution of that image is more and that includes information of more materials of land cover. And that spectrum is a mixed spectrum [28].

Contribution of pure spectra in this mixed spectrum is Endmember spectra. The above figure depicts mixture space is the mixture of Spectral bands A, B and C. Spectral mixtures of two types, macroscopic mixture and intimate mixture. Each photon in macroscopic mixture relates with one surface material.

In this reflection of each material is combined additively. Contribution of material directly proportional to area within pixel. The above figure shows this type of mixture which is a combined work of bare soil and vegetation. Intimate mixture is a microscopic mixture of mineral materials in soil. More than one material interacts with a single photon.

1.4. Reflectance Conversion

For the comparison of Hyperspectral image spectra with the reference spectra radiance value need to be converted to reflectance value. This conversion is necessary due to sensor gain, topography and atmospheric transmission [29].

Field researchers of Hyperspectral imagery use Empirical line method in order to convert image data to reflectance of an image area. In this method a linear equation related to radiance to reflectance is derived from the reflectance of target areas. To recognize these target areas these should be specified by different brightness.

To convert each image band to the reflectance combined effect of additive component, i.e. offsets and multiplicative radiance factor i.e. gain has to be taken. Because of conversion doesn't take effect of topography final values are apparent reflectance values.

1.5. Strategies for Image Analysis

Analyzation of Hyperspectral images is a challenge for Hyperspectral remote sensors. Spectral properties of surface materials can be characterized from the finer spectral resolution of Hyperspectral images obtained by above sensors [30]. Two adjacent spectral bands have nearly same information and their spectral signatures nearly identical.

Even though some of information of image data is seemed to be unnecessary but, installed information contains good data of ground surface materials [30]. An active research of Hyperspectral scene is analyzed and visualizing of information by using correct approaches and tools. Typically, Analyzers of Hyperspectral images concentrate on spectral information than spatial information.

1.6. Defining of Image Endmembers

Each endmember in Hyperspectral image represents a single pure material. Dimensionality of the Hyperspectral image data set is needed to be reduced since the correlation degree between spectral bands of adjacent is high. Minimum noise fraction reduces dimensionality of Image data set [31].

Minimum noise fraction transform avoids noise components and retains noise free components. The Pixel purity index algorithm is applied to extreme spectra of minimum noise components. It inspects transmitting outward of a progression of haphazardly situated bearings from the beginning of the direction space. Extreme spectra can be obtained [32] by projecting spectral points onto the test vector. Edges of minimum noise fraction are the pixels with high values in the pixel purity index.

1.7. Application of Hyperspectral Imaging

It is used in different fields like

- surveillance,
- Disaster management,
- Biological equality,
- Precision Agriculture,
- Biotechnology, Environmental monitoring,
- Food,
- Pharmaceuticals,
- Remote sensing,
- Security and defense,
- Thin films.
- Military target observing and
- Fringe observation.

1.8. Preprocessing of images

Deal with remotely sensed hyperspectral images offer an enormous amount of data about the area of survey. But the sensors being too far from the object the information noted on the sensors. So it is clear that the information noted on the sensors are not exactly the true data

[33], and there are some corrections to be built to get the true data and study it. Though direct examine of recorded data contributes certain results, it is better to pre-process the information, modify them, and near them to the true data and then study it [15].

The pre-processing consists of changing digital numbers to radiance, radiance to Exo-atmospheric reflectance data and dimensionality reduction. Further noise reduction techniques like PCA, MNF are considered. Hyperion sensor offers an image set of 220 spectral bands from 0.4 microns to 2.5 microns with 30-meter resolution [33]. Hyperspectral imager of Hyperion sensor can capture an image of 7.5km to 100km with 242 spectral band radio metrically accurate. Hyperspectral images taken at two different times. Conventional change location strategies like picture differencing, Change vector investigation and picture apportioning uses just a solitary band. These methods don't use several spectral bands i.e. these methods don't use the richness of spectral information. So the task is developing a suitable method that can identify changes between two Hyperspectral images taking advantage of several narrow resolution spectral bands over the electromagnetic spectrum in the regions of the visible and infrared spectrum.

1.9. Literature review

From verification of proper applicable handling techniques of Hyperspectral change detection a brief study of existing change detection techniques are presented here. These techniques are used in different applications.

1) Bruzzone *et al*. (2002) [3], depicts a technique for change location in remote detecting pictures.It creates a Binary change map by taking two spectral bands. This change map depends on Threshold value. If difference image spectral signature value is greater than threshold value, then that spectral signature comes under category changed pixel

otherwise No changed pixel. Selection of the threshold depends on statistical values of different image.

2) Wiemker et al. (1997) [4] describes change detection using principal component analysis. It takes each image as a vector form. Feature space is created by principal component analysis of two image vectors. Feature space obtained from these two vectors is bi-temporal feature space since first vector represents pixel estimations of picture at time 1 and second vector speaks to pixel estimations of picture at time 2. From the principal component analysis of this bi-temporal feature space No changed pixels lie under first principal axis, whereas Changed pixels lie under second principal axis. To generate a Binary change map or No change map a threshold value is selected by the Bayes decision rule. Bayes approach is an unsupervised classification approach. It classifies all pixels into two classes, one is change pixel class and the second is No change pixel class.

3) Nielsen *et al.* (1998) [5] describes change detection using Multivariation alteration detection.It works according to Canonical correlation Analysis. From the orthogonal components (i.e., these are showing maximum variance) of the difference between linear combinations of spectral signatures of two images Change or No change map is generated by selecting a threshold value according to Bayesian approach.

4) Borrego *et al.* (2001) [6] describes change detection using change vector analysis method. Analysis of this method depends on two variables One if Magnitude of change vector which is obtained by calculating Euclidian distance between pixels of two images of same spatial position and the second is an angle vector of two images. This Angle represents type of change. In a bad position is inadequacy of dividing pixels of changed and unaltered of contrast picture subsequent to unsupervised systems don’t utilize

reference information set. This sort of qualification impacts consistency and precision of progress recognition and it is overcome by either experimentation strategy or practical technique. This paper utilizes two techniques [34] to conquer this negative angle. One system takes the suspicion that the pixels of distinct picture are autonomous one another so it takes the programmed arrangement for threshold selection. Other technique considers information identified with spatial which incorporates neighborhood of every pixel of distinct picture.

5) Prashanth Marpu *et al.* (2001) [7] describes change detection using is iteratively reweighted multivariate change detection. It utilizes basically two ideas one is principal component analysis for decreasing dimensionality of Hyperspectral image and other one is iteratively reweighted multivariate change detection. It embraces highlight diminishment for change identification. This approach is clarified utilizing two Hyperspectral image data sets and results have a decent relationship with the field perceptions.

1.10. Problem statement

Typically Hyperspectral images are taken at different at spectral wavelength bands. So changes may occur either in temporal domain or in spectral domain or both. It is very important what spectral bands are taking for detecting changes.

An m-dimensional Hyperspectral image contains m-spectral wavelength bands. Most of change detection algorithms, certain number of bands for particular applications. This work uses most of spectral bands for change detection in Hyperspectral images. Increase in utilization of bands increases the utilization of spectral signatures.

1.11. Objectives

- Detection of changes in land cover over a large geographical area with the implementation of an effective change detection algorithm.
- With the help of Hyperspectral images, providing a good environment in change detection.
- Effective utilization of spectral signatures of Hyperspectral images for change detection.
- By using unprecedented style of Hyperspectral imaging explore the possibility of changes.

1.12. Thesis Overview

- Chapter 1 describes thesis motivation, problem statement, thesis objectives and Literature review and concepts of Hyperspectral Imaging
- Chapter 2 describes the method of Change detection using principle component analysis.
- Chapter 3 describes the method of Change detection using Hierarchical method.
- Chapter 4 describes conclusion and future discussion of thesis

Chapter 2

Change detection using k-means clustering

2.1. Introduction

Change identification routines could be arranged as either regulated or unsupervised as indicated by the way of information preparing. The previous is in view of a managed arrangement strategy, which requires the accessibility of a ground truth with a specific end goal to determine a suitable preparing set for the learning procedure of classifiers. The last approach, which is received in this letter, performs change location by making an immediate examination of two multitemporal pictures considered without fusing any extra data [1]. Unsupervised change recognition systems primarily utilize the programmed investigation of progress information which are built utilizing multitemporal pictures.

The majority of the unsupervised routines are created in view of the picture differencing. Picture differencing-based calculations full fill the change location by subtracting, on a pixel premise, the pictures procured at two time occurrences to deliver new picture called distinction picture [1]. The registered contrast picture is such that the estimations of the pixels connected with area cover or area utilization changes present values fundamentally not quite the same as those of the pixels connected with unaltered territories. Changes are then recognized by breaking down the distinction picture.

A computationally straightforward yet viable programmed change location technique is offered by dissecting the distinction picture of two satellite pictures procured from the same zone scope however at two diverse time examples [1]. The nonoverlapping squares of the distinction picture are utilized to concentrate eigenvectors by applying principal circuit analysis. At that point, a component vector for every pixel of the distinction picture is removed by anticipating neighborhood information onto eigenvector space. The component vector space is bunched into two bunches utilizing k-implies calculation. Every group is spoken to with a mean component vector [1]. At long last, change discovery is accomplished by allocating every pixel of the distinction picture to the one of the groups as per the base Euclidean separation between its element vector and mean component vector of the bunches.

2.2. Methodology

In this method the difference image is divided into $b \times b$ non-overlapping blocks $S, S \leq b^2$. Orthonormal eigenvectors space is extracted through principal circuit analysis of $b \times b$ non-overlapping block set to form an eigenvector space [1]. Every constituent within the distinction image is drawn with an S - dimensional feature vector that is that the projection of $b \times b$ difference image information onto the generated eigenvector area [1]. The change detection is achieved by partitioning the feature vector [35] [1] space into 2 clusters victimization k-means clustering with k = 2 then assignment every constituent to the one amongst the 2 clusters by victimization the minimum geometer distance between the pixel's feature vector and mean feature vector of clusters [1].

2.3. Steps of algorithm

- Difference image creation.
- From difference image creation of blocks of images of size $b \times b$ [1].
- Utilizing Principal component analysis generation of eigen vector space of image blocks.
- From the projection of overlapping blocks on each pixel generating feature vector space.
- Utilizing k-means algorithm clustering feature vector space into two clusters. From minimum Eucledian distance between feature vector and mean feature vector assigning of each difference pixel to one of two clusters [1].

2.4. Procedure

The difference image of two images acquired at time t_1 and t_2 is

$$\mathrm{Y_d} = |Y_1 - Y_2|$$

Where X_1 and X_2 are the images taken at time t_1 and t_2

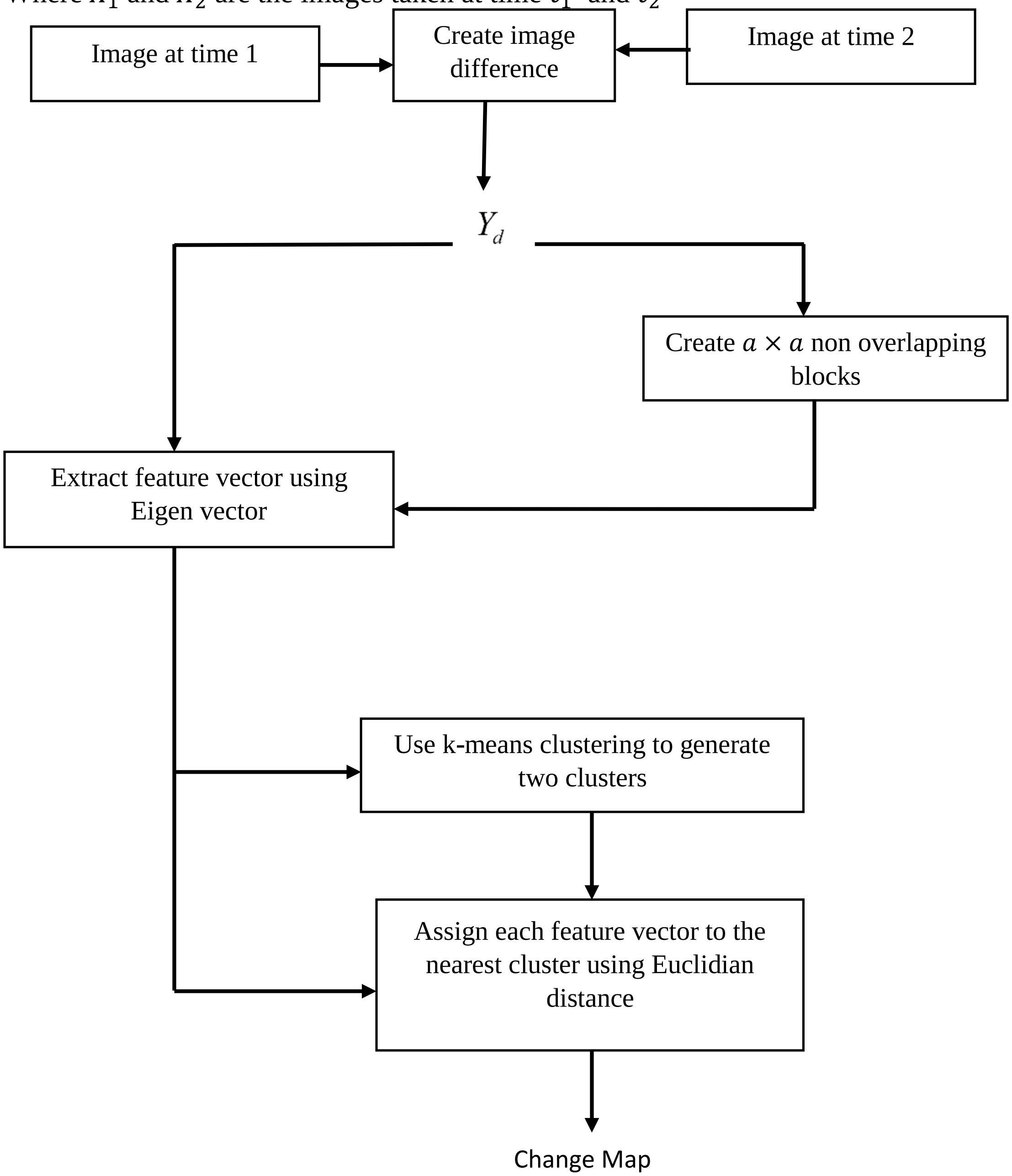

Figure 2-1General schematic diagram

Eigenvector space is created by using Principal component Analysis [1] of the block$Y_d(x, y)$. The main functions of a principal circuit analysis is the analysis of knowledge to spot patterns and finding patterns to cut back the size of the dataset with lowest loss of data [1]. Here, our desired outcome of the principal part analysis is to project a feature area (our knowledge set consisting of n x d-dimensional samples) onto a smaller topological space that represents our data "well".

A attainable application would be a pattern classification task, wherever we would like to cut back the procedure prices and also the error of parameter estimation [36] by reducing the amount of dimensions of our feature area by extracting a topological space that describes our knowledge "best" [12].

The Average vector [1] of every block is calculated by,

$$\phi = \frac{1}{N}\sum_{b=1}^{N} Y_b^d$$

Where $Y_b^b = Y_d(x, y)$ and b is an index with $1 \le b \le N = \lfloor A \times B / a \times a \rfloor$

Differenced vector [1] from average vector is

$$\alpha_b = Y_b^d - \phi$$

To create Eigenvector space [1] it is necessary to calculate covariance matrix of α_b

$$\beta = \frac{1}{N}\sum_{b=1}^{N} \alpha_b \alpha_b^T$$

Feature vector space of $Y_d(i, j)$ is obtained from the projection of $Y_d(i, j)$ on to the Eigen vector [1].

$$u(i, j) = [u_1 \, u_2 \, u_3 \, ... u_s]^T$$

Where $1 \le S \le h^2$

$$u_s = e_s^T (Y_d(i, j) - \phi), 1 \le s \le a^2$$

S is the dimension of feature vector $u(i, j)$

The next stage of this method is the generation of 2 clusters using k-means clustering with k=2 by clustering the feature vector space.

When there's a modification between 2 pictures during a specific region, then it's expected that the values of the distinction image pixels therein region are higher than the values of pixels [1] within the regions wherever there's no change. So, the pixels with low average value of difference image are considered as unchanged pixels and these pixels are assigned to unchanged class [1] γ_u and if the pixels with high average [37] value of difference image are considered as changed pixels and these pixels are assigned to changed class [1]γ_c. And the binary change Map [1] is given by

$$f(i,j) = \begin{cases} 1, & \left\| u(i.j) - u_{\gamma_c} \right\|_2 \leq \left\| u(i.j) - u_{\gamma_u} \right\|_2 \\ 0, & othewise \end{cases}$$

Where u_{γ_c} the cluster is mean feature vector [1] of class γ_c and u_{γ_c} is the cluster mean feature vector of classγ_c. Performance of this method is calculated by two parameters, percentage error [1] and stability value [1].

Stability of this algorithm is calculated by measuring the difference [1]between two change detection results [1]. For a given two Hyperspectral images Y_1andY_2, to generatef_1. Then, to find change map [1] f_2 , X_1 is contaminated with noise. The difference [1] between f_1 and $f_2$is

$$\lambda = 1 - \frac{\sum_{a=1}^{P} \sum_{b=1}^{Q} \sum_{c=1}^{R} |f_1(a,b,c) - f_2(a,b,c)|}{PQR}$$

This τ value reflects the robustness of the change detection algorithm against noise [1]. When f_1 and f_2 are the same, λ becomes one, and it approaches to zero when f_2 differs fromf_1.

2.5. Experimental Results and Discussions

a) b) c)

Figure 2-2 Hyperspectral image acquired over the Yangtze river in china obtained from U.S.G.S website a) and b) images acquired in 1993 and 2013 c) Change Map h=8

Above figure depicts change map of two images of Yangtze River in china taken at 1993 and 2013 respectively. In change map black color represents no change and white color represents changes between two images.

Table 2-1 Percentage error and stability value of Yangtze river for different block size

Block size(h)	% error	λ
1	2.2685	0.9881
2	2.2164	0.9888
3	2.2079	0.9890
4	1.9896	0.9913
5	1.8167	0.9938
6	1.4268	0.9952
7	1.3068	0.9956
8	1.1146	0.9973
9	1.0676	0.9978
10	0.9251	0.9979
11	0.9190	0.9980
12	0.6111	0.9981
13	0.4323	0.9983
14	0.1148	0.9988
15	0.0781	0.9991
16	0.0212	0.9999

Above table depicts for different block values of difference image percentage errors and stability values. With the increase of block values percentage error is decreasing and stability value is increasing.

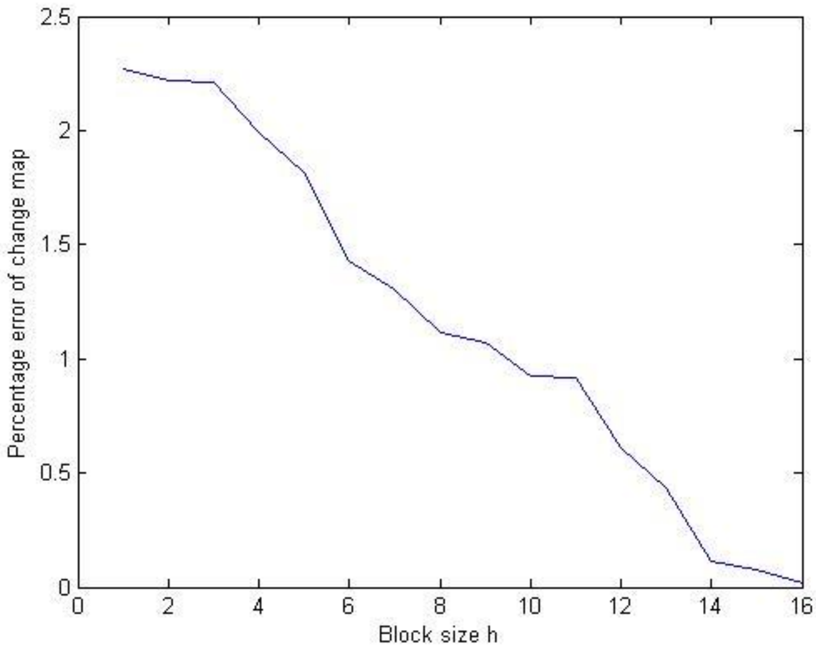

Figure 2-3Block size v/s Percentage of change map of Yangtze river

a) b) c)

Figure 2-4 Hyperspectral image acquired over the salt lake in china obtained from U.S.G.S website a) and b) images acquired in 1993 and 2013 c) Change Map h=8

Above figure depicts change map of two images of Saltlake in India taken at 1993 and 2013 respectively. In change map black color represents no change and white color represents changes between two images

Table 2-2 Percentage error and stability value of salt lake for different block size

Block size(h)	% error	λ
1	2.9784	0.9877
2	2.7696	0.9918
3	2.1700	0.9922
4	2.1632	0.9927
5	1.8213	0.9943
6	1.6024	0.9951
7	1.5732	0.9954
8	1.4645	0.9971
9	1.4471	0.9977
10	1.3601	0.9977
11	1.0615	0.9978
12	0.9615	0.9980
13	0.3558	0.9981
14	0.3352	0.9985
15	0.1906	0.9987
16	0.1346	0.9992

2.6. Summary

An unsupervised change identification method is created by leading k-means bunching on highlight vectors which are removed utilizing $b \times b$ nearby information projection onto eigenvector space. The eigenvector space is produced utilizing principal circuit analysis on $b \times b$nonoverlapping distinction picture pieces. This technique utilizes $b \times b$ neighborhood to concentrate highlight vector for every pixel so that it consequently considers the logical data.

Chapter 3

Change detection using Hierarchical method

3.1. Introduction

The new generation of satellite hyperspectral sensors will acquire terribly elaborated spectral info directly connected to land surface materials. Thus, dealing with hyper spectral images gives us several potential changes in land covers [35]. Hierarchical method addresses the change-detection problem in multitemporal hyperspectral remote sensing pictures, analyzing the quality of this task.

A unique hierarchical change detection approach is proposed, that is aimed toward characteristic all the attainable change classes present between images [2]. In larger detail, in order to formalize the change detection in hyper spectral images, an analysis of the conception of "change" is given from the angle of pixel spectral behaviors [2].

The method hierarchical change detection is developed by considering spectral change info to spot the change categories having distinguishable spectral behaviors [2]. Because of the way that, in genuine applications, reference samples area unit usually not available, this approach is meant in an unsupervised way.

With a specific end goal to direct viable change location in hyper phantom pictures, it's imperative to get it and model the idea of modification in multitemporal hyperspectral pictures and its relationship with the idea of endmember [36]. The terribly high spectral resolution makes it doable to notice many variations within the spectral signatures of pixels non inheritable in a scene of interest. Such variations might occur at completely different spectral resolution levels.

3.2. Pseudo Binary Change detection

Y_1 and $Y_2$are two hyper spectral images with size $A \times B$, acquired on an equivalent geographic region now and then $time_1$ and $time_2$, respectively.

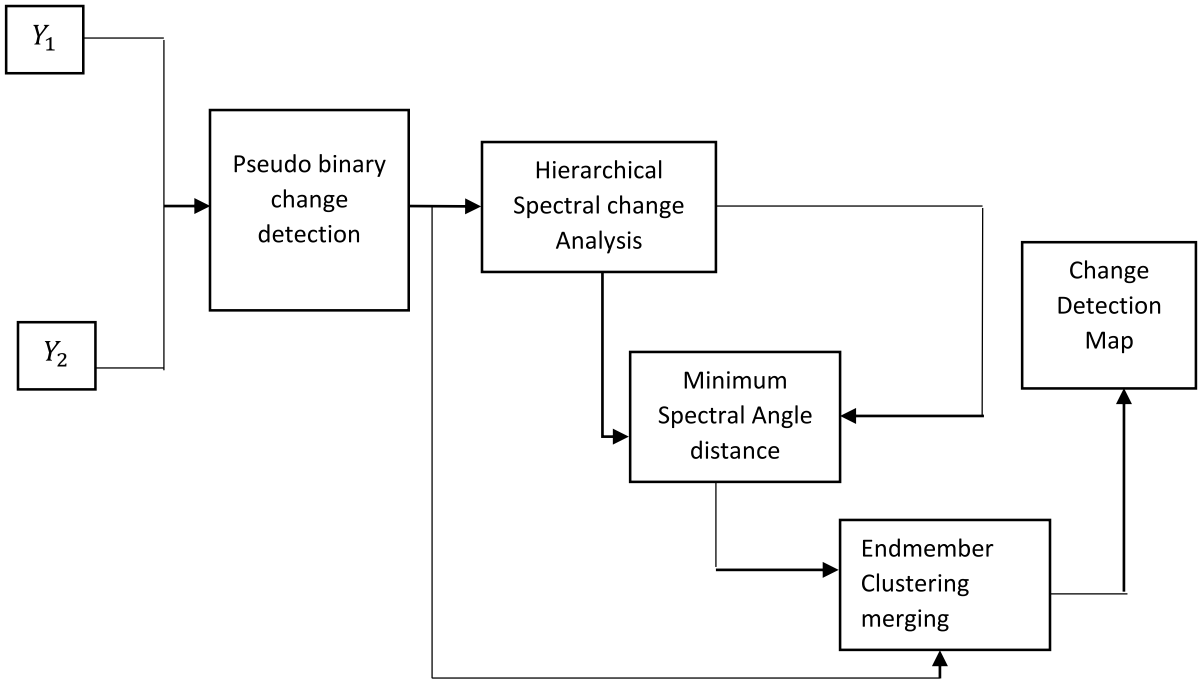

Figure 3-5 Block Diagram of Hierarchical method

To investigate the behaviors of spectral variations between the 2 pictures, allow us to calculate the Hyper spectral distinction image [2] Y_d by subtracting images from each other by pixel wise [2], i.e.,

$$Y_d = |Y_1 - Y_2|$$

Where Y_1 is image taken at time $time_1$and $time_2$is image taken at time $time_2$

However, it is referred as pseudo binary as a result of the output has 3 classes [2]. Category of changed pixels [2] γ_c, category of no-change pixels [2] γ_n and category of unsure pixels [2] γ_u. The category of changes Ω_c is employed to initialize the foundation node of a tree structure for change illustration [2].

From X_d, the magnitude and therefore the direction of spectral change vectors will be extracted. Within the initiative of the planned methodology, we are only fascinated by characteristic [2] γ_c from [2] γ_n. Thus, only the magnitude λ is taken into account, i.e.

$$\lambda = \sqrt{\sum_{a=1}^{S} (Y_d^a)^2}$$

where S denotes the quantity of spectral channels of the hyperspectral images (i.e., the spatiality of spectral change vectors), andY_d^a is the a^{th} spectral distinction in Y_d. Thus, the entire amendment information [2] is compressed into a 1-D feature [2]. The explanation behind this selection is as follows:

1) To alter and avoid any feature choice procedure and

2) To take advantage of the contribution of all parts of the spectrum [2]

Changed and unchanged pixels area unit separated into 2 teams according to a threshold worth P_λ computed on the magnitude variable [2]. The Bayesian decision theory is applied to seek out this threshold. The expectation maximization rule [37] is employed for estimating the category applied math parameters (i.e., the class prior possibilities, the mean values, and also the variances) in associate degree unsupervised approach. Multiple changes area unit approximated jointly single modification category γ_c [2] in the magnitude domain to focus solely on the final modification information [2]. This approach has been wide utilized in binary change detection with multispectral pictures and incontestable to be an approximation in hyper spectral pictures [2]. The approximation is appropriate as this can be solely a preliminary step.

In order to cut back the impact of attainable thresholding errors [2]and obtain conservative results that don't propagate important errors within the next steps, a margin δ is ready on the brink computed on the histogram $h(\gamma)$ of the magnitude γ, and 3 categories area unit outlined. The 3 categories area unit as follows [2].

1) **Category of unsure pixels $\boldsymbol{\gamma_u}$**, [2] on that it's inconceivable to take a reliable call at this level of the process. These pixels are going to be analyzed and reclassified according to the generated endmembers.

2) Category of modified pixels $\boldsymbol{\gamma_c}$, [2] which has pixels having a high likelihood to be modified, however with none information on their kind. The matter of the multiple changes identification is going to be addressed within the next step by the spectral change analysis method.

3) Category of unchanged pixels $\boldsymbol{\gamma_n}$, [2] that solely contains pixels having a high likelihood to be unchanged. These pixels area unit treated as a pure no-change category endmember due to their low magnitude.

Thus, for a given spectral change vector y_i in Y_d, a label is appointed in line with the subsequent rule:

The matter are often addressed by victimization clustering strategies to mechanically notice the various modification classes [2]. However, the matter of multiple-class separation in hyper spectral pictures is far harder than in multi spectral pictures. This is as a result of the subsequent issues:

1) The high spectral resolution makes the spectrum a lot of sensitive to changes; therefore, a high number of changes can be detected; and

2) Refined changes within major changes area unit perpetually troublesome to be directly known from γ_c.

3.3. Hierarchical tree

Depending on how the specific quite modification wedged on the spectral signature spectral change vectors [2] is preliminary separated into major changes. Major changes [2] in the main rely on the land cowl category transitions [38] and have an oversized spectral distinction with relation to no-change category and among one another [2]. Usually, major changes is simply and directly known as they considerably have an effect on an oversized portion of the spectrum of hyper spectral pictures [2].

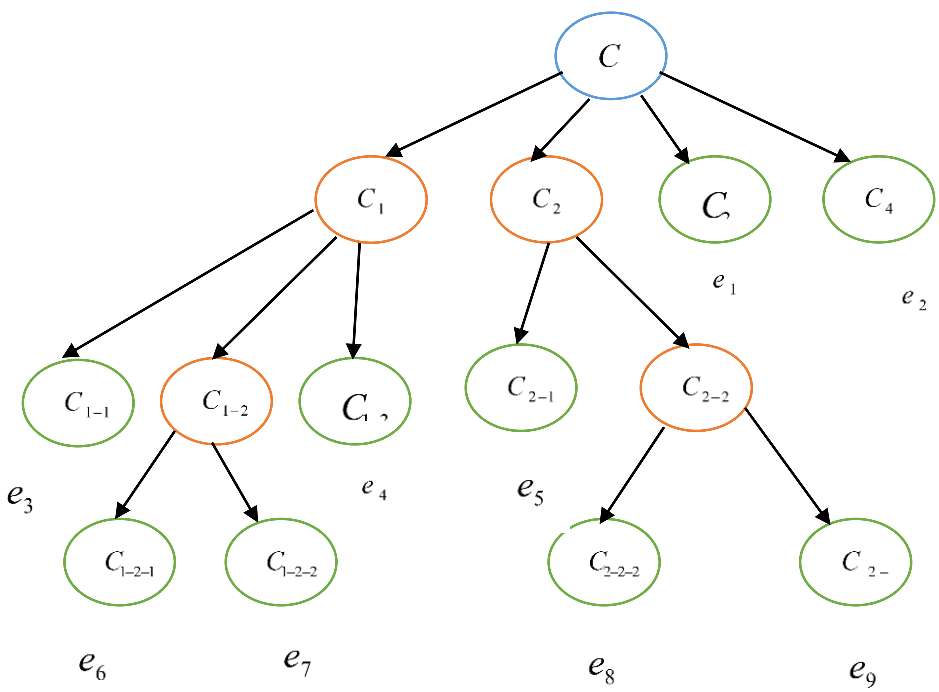

Figure 3-6Hierarchical tree

Each major change produces statistically vital different spectra compared with one another and with the category of unchanged pixels [2]. Among every major modification [2], betting on the data, it's potential to notice alternative clusters of pixels having significant applied math variations in some elements of the spectrum [2]. Such clusters area unit outlined here as delicate changes. Delicate changes [2] have spectral change vectors just like a significant modification [2], however disagree from it in small parts of the spectrum.

To overcome the preceding issues, we have a tendency to propose an answer based on the concept of rotten the first advanced drawback into sub problems by a gradable spectral apoplexy. The gradable structure is sculptural by a tree of changes [2] outlined to drive the analysis. Let $L_d$be a generic level within the tree structure with $d = 1,2,3, \dots \dots \dots . . D - 1$.

The depth of the tree is D. The most plan is to start out from the basis node [2] within the prime level (i.e., L_0 that represents the overall change category [39] Ω_c known within the pseudo binary change detection step) and gradually separate completely different types of develop into kid nodes by selectively exploiting the spectral info [2]. At the essential level (i.e., L_1) of the tree, the need is given to recognize the key changes that, have significant spectral distinction from one another [2].

Inside every child node, delicate changes (if any) are detected and separated. This method is iterated till all modification endmembers (i.e., leaves of the tree) are found. Let us think about the basis node that contains all the modified pixels [2] with none distinction concerning their kind [2]. To model the spectral homogeneity of γ_c, a similarity evaluation supported the spectral angle distance is employed. The spectral angle distance θ is computed between every y_i in γ_c, and a reference spectral signature S_{γ_c} is calculated because the average of all the y_i in γ_c.

$$u(y_i, S_{\gamma_c}) = arccos\left(\frac{\sum_{a=1}^{s} y_i^a S_{\gamma_c}^a}{\sqrt{\sum_{a=1}^{S}(y_i^a)^2}\ \ \sqrt{\sum_{a=1}^{S}\left(S_{\gamma_c}^a\right)^2}}\right)$$

Where y_i^a and $S_{\gamma_c}^a$ are the a^{th} part in y_i and $S_{\gamma_c}^a$, respectively. For every y_i, the smaller the $u(y_i, \gamma_c)$, the higher the similarity [2] with the reference spectrum and the higher the $u(y_i, \gamma_c)$, the smaller the similarity with the reference spectrum [2].

For a pure modification endmember, it is expect that each one spectral change vectors [2] have terribly similar spectral behaviors. Thus, to verify the homogeneity of γ_c, it is to compare the standard deviation σ_{γ_c} of $u(y_i, \gamma_c)$ with a threshold p_σ. If σ_{γ_c} is smaller than p_σ, the modification category [2] is taken into account as being homogenized, a change endmember [2] is detected. Consequently, the method is in convergence, and also the tree solely includes a single node [2]. Otherwise, the amendment category is taken into account as being heterogeneous and likely to contain more than one change endmember [2]. Therefore, the hierarchical decomposition starts.

To distinguish major changes [2] in Ω_c, principal circuit analysis and clustering is used. [2] However, the other transformation technique can be thought-about. Note that PCA is applied solely to the y_i of γ_c. This way, we have a tendency to optimize the illustration of the changes [17]. Then, the set of changed principal parts that includes over ninety fifth of modification data to reject the noise and redundant data [40]. This alternative additionally reduces the computational complexness.

Once the main modification categories in γ_c are recognized and separated by mistreatment the adopted bunch algorithmic rule [2], the root node splits into totally different leaf nodes at L_1 within the tree. Every node corresponds to 1 major modification category [2] (i.e. $\gamma_{c_1}, \gamma_{c_2}, \gamma_{c_3}, \ldots$). For every major modification $\gamma_{c_1}, \gamma_{c_2}, \gamma_{c_3}, \ldots$, the spectral homogeneity of spectral change vectors is tested in keeping with spectral angle distance [2].

As an example, allow us to contemplate the primary node associated to category ω_{c_1}. The spectral angle distance [2] of γ_{c_1} is computed as $u\left(y_i, S_{\gamma_c}\right)$ for each $y_i \epsilon \gamma_{c_1}$. If for a given node convergence isn't reached, then all the preceding operations (i.e., PCA, clustering, and stop criterion evaluation) [2] square measure iterated by considering solely the spectral change vectors [2] of pixels x_i within the thought of node (e.g., γ_{c_1}in our example) [2].

Once all the nodes at L_1 square measure processed, the algorithmic rule moves to consequent level. The stratified decomposition is applied to every node in every level of the tree till the convergence is reached for all of them [35]. This happens once all the nodes satisfy the Homogeneous condition [2]. The last node of every branch is a leaf node and corresponds to 1 modification endmember [2] in $\gamma_e = \{e_1, e_2, \ldots \ldots \ldots \ldots e_n\}$ [2].

3.4. Generation of Change Map by Endmember cluster merging

After distinguishing E modification endmembers $\gamma_e = \{e_1, e_2, \ldots \ldots \ldots \ldots e_n\}$, the pixels within the unsure category [40] Ω_u derived within the pseudo binary change detection [2]. These pixels area unit assigned to one of the modification endmembers [2] or to the no-change category [2] on the idea of spectral similarity [2]. Spectral angle distance [2] is computed between the spectral change vector y_i, $x_i \epsilon \gamma_u$ and also the reference spectra S_{e_j} (i.e., the typical spectrum of every detected modification endmember in γ_e and of the no-change endmember γ_n) [2]. Then, y_i is assigned to the category with the minimum distance value, i.e.

$$y_i \epsilon argmin\left\{u\left(y_i, S_{e_j}\right)\right\}$$

$e_j \epsilon \{\gamma_e, e_n\}$Where $u\left(y_i, S_{e_j}\right)$ denotes the spectral angle distance [2] between $y_i, y_i \epsilon \gamma_u$ and a given reference spectrum [2] S_{e_j}. A definitive change recognition guide [2] is created by combining the outcomes got inside of the 3 arrangements of changed, indeterminate, and unaltered pixels [2].

3.5. Experimental Results and Discussions

a) b) c)

Figure 3-7 Hyperspectral image acquired over a Yangtze river in china obtained from U.S.G.S website a) and b) images acquired in 1993 and 2013 c) Change Map using Hierarchical method

Above figure depicts change map of two images of Yangtze River in china taken at 1993 and 2013 respectively. In change map black color represents no change and white color represents changes between two images.

Table 3-1 Details of Threshold values of Yangtze river

Total no of Bands	Pre-processed bands	$T(\rho)$	δ	T_s	Endmembers
225	170	10	5	0.03	7

Above table depicts threshold values used in Hierarchical change detection method and number of change endmembers obtained during change detection.

Table 3-2 Percentage of End member accuracy of Change map of Yangtze river

Endmember accuracy (%)							Total no of error pixels
e_1	e_2	e_3	e_6	e_5	e_6	e_7	192
96.0001	78.3015	89.7803	94.1704	61.0926	99.5201	100	

Above table depicts percentages of change endmembers obtained.

a) b) c)

Figure 3-8 Hyperspectral image acquired over a saltlake obtained from U.S.G.S website a) and b) images acquired in 1993 and 2013 c) Change Map

Above figure depicts change map of two images of Saltlake in India taken at 1993 and 2013 respectively. In change map black color represents no change and white color represents changes between two images

Table 3-3 Details of Threshold values of salt lake

Total no of Bands	*Pre-processed bands*	$T(\rho)$	δ	T_s	*Endmembers*
225	*170*	*5*	*3*	*0.05*	*5*

Table 3-4 Percentage of Endmember accuracy of Change map of saltlake

Endmember accuracy (%)					Total no of error pixels
e_1	e_2	e_3	e_4	e_5	201
70.0791	82.6524	94.3172	84.1210	98.6719	

3.6. Summary

The change endmembers are continuously perceived by examining the unpleasant properties in the otherworldly change vector area. Additionally, the dynamic examination can recognize the discriminable powerful change endmembers from coarse to fine level inciting a predominant model. The essential responsibilities of this hypothesis are according to the accompanying: 1) examination and importance of the thought of changes in Hyper ghastly mages, by considering the refinement of spooky change rehearses in the Spectral change vector zone at particular large purpose of interest scales

Chapter 4
Conclusions and Future Works

4.1. Conclusions

This method is examined the change detection of bi-temporal Hyper spectral images. By considering the inborn intricacy of the Hyperspectral information, a fitting meaning of the idea of progress in Hyperspectral images is given, and the idea of progress endmembers is presented. The change endmembers are progressively recognized by investigating the ghastly properties in the spectral change vector domain. Besides, the progressive investigation can distinguish the discriminable otherworldly change endmembers from coarse to fine level prompting a superior model. The primary commitments of this theory are as per the following: 1) examination and meaning of the idea of changes in Hyper spectral mages, by considering the distinction of ghostly change practices in the Spectral change vector area at distinctive phantom point of interest scales; and 2) A methodology that models the discovery of various changes in a progressive manner, to distinguish the change data and separate various types of changes (real change, unpretentious change, and, at last, change endmembers) as indicated by their otherworldly contrast. This makes it conceivable to find the distinction among comparable changes by diminishing the trouble of recognition. Additionally, it is outlined in an unsupervised way; hence, it fits a large portion of genuine applications, for which frequently the ground truth is not accessible.

4.2. Future Works

As future advancement of this work, the heartiness of this technique will be tried on the accessible multitemporal Hyperspectral pictures indicating contrasts in brightening conditions and no genuine change. Also, we plan to 1) consider in the proposed strategy likewise the spatial data with a specific end goal to expand the strength and the precision of the change discovery comes about, 2) characterize a solid programmed method for the recognition of the previously .

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